A value-based perspective on supporting and hindering factors for research data management

Citation for published version:
Wilms, KL, Stieglitz, S, Ross, B & Meske, C 2020, 'A value-based perspective on supporting and hindering factors for research data management', *International Journal of Information Management*, vol. 54, 102174, pp. 1-12. https://doi.org/10.1016/j.ijinfomgt.2020.102174

Digital Object Identifier (DOI):
10.1016/j.ijinfomgt.2020.102174

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Publisher's PDF, also known as Version of record

Published In:
International Journal of Information Management

International Journal of Information Management 54 (2020) 102174

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Research Note

A value-based perspective on supporting and hindering factors for research data management

Konstantin L. Wilms[a], Stefan Stieglitz[a,*], Björn Ross[a], Christian Meske[b]

[a] Department of Computer Science and Applied Cognitive Science, Faculty of Engineering, University of Duisburg-Essen, Duisburg, Germany
[b] Digital Transformation & Strategic Information Management, School of Business & Economics, Freie Universität Berlin, Germany

A R T I C L E I N F O

Keywords:
Knowledge management
Data sharing
Knowledge sharing
Higher education
Research management

A B S T R A C T

Research data management (RDM) is an important prerequisite for a substantial and sustainable contribution to knowledge. There is a pressing need to examine why researchers hesitate to store, annotate, share and manage their research data. To model underlying psychological factors influencing researchers' refusal to conduct RDM, the social exchange theory is extended with elements from prospect theory. Thus, it allows psychological insights into researchers' decision-making, and illustrates the role of cost and benefit evaluations under uncertainty. Data management policies of a major funding agency were presented to a homogeneous group of researchers from the Information Systems community in Germany. The findings show that many researchers see a high value in RDM but are still held back by uncertainty. While the benefits seem to outweigh the costs, we ascertain the uncertainty factors which hinder researchers' intention from conducting RDM in the future. The perceived fear of losing control over one's data is identified as a major hindering factor, while the fear of losing one's unique value did not prevail. The study provides novel insights for executives, administrators, and developers in higher education institutions, which are especially important for furthering RDM implementation strategies, as well as for system development.

1. Introduction

Along with the proliferation of data-intensive research processes, for example via online experiments, survey data as well as simulations and sensor measurements, enormous amounts of varied research data are generated and collected continuously (Chalmers, 1978; Sadiq & Indulska, 2017; van der Aalst, Bichler, & Heinzl, 2017). Researchers and institutions of higher education (HE) repeatedly reach their limits when managing and storing research data, a circumstance that has already led to huge data losses or to the inability to provide annotated research data for reuse (e.g. Savage & Vickers, 2009; Vines et al., 2014; Blumenthal, 2017). In order to cope with the growing flood of digital data, governments and funding agencies have started to call on research disciplines to embrace adequate research data management (RDM) (Ahmadi, Jano, & Khamis, 2016; Combita Niño, Cómbita Niño, & Morales Ortega, 2018; Link et al., 2017; Perrier et al., 2017). RDM can be described as a form or prerequisite of knowledge management, which consists of the initiatives, processes, strategies and systems that support and improve the storage, evaluation, sharing and refinement of data to create knowledge (Makani, 2015).

In this regard, several international research funding institutions, such as the National Science Foundation (NSF) or the Deutsche Forschungsgemeinschaft (DFG; German Research Foundation) have set up mandatory RDM policies, compliance with which is a basic prerequisite for future funding (Wilms, Stieglitz, Buchholz, Vogl, & Rudolph, 2018). Comprehensive RDM encompasses, for example, the long-term storage and annotation of research data, but also making the data accessible and usable by anyone, a concept also known as open data (Link et al., 2017; Wilms, Stieglitz, Buchholz et al., 2018). While there is an increasing pressure on higher education institutions to promote RDM, there is still a great deal of mistrust across several academic fields when it comes to recording, preserving, and sharing research data (Borgman, 2012; Perrier et al., 2017; Piwowar, 2011; Sayogo & Pardo, 2013).

Since recent publications only point out minor attention towards RDM by scholars (Rudolph, Thoring, & Vogl, 2015; Sayogo & Pardo, 2013; Wilms, Stieglitz, Buchholz et al., 2018), a gap can be identified between the responsibility of universities to prioritize the topic and researchers' actual data management. Consequently, there seems to be a pressing need for research to analyse what factors influence researchers' decision to conduct RDM. According to the Social Exchange Theory (Homans, 1958), which has successfully been applied in the

* Corresponding author at: Department of Computer Science and Applied Cognitive Science, Faculty of Engineering, University of Duisburg-Essen, Forsthausweg 2, 47057, Duisburg, Germany.

https://doi.org/10.1016/j.ijinfomgt.2020.102174
Received 4 April 2019; Received in revised form 12 June 2020; Accepted 12 June 2020

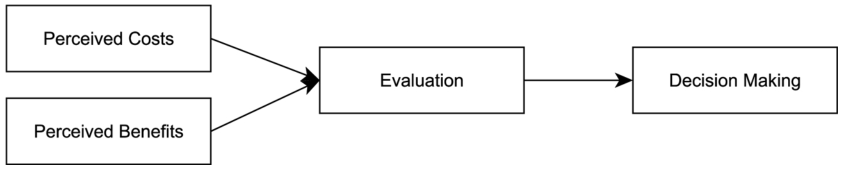

Fig. 1. Social exchange theory by Homans (1958).

context of knowledge exchange (e.g. Liang, Liu, & Wu, 2008), individuals comply with knowledge management strategies by weighing up the advantages and disadvantages. The individual will immediately consider the loss involved in changing their current behaviour and decide against the new strategy (i.e. following new RDM guidelines) if the disadvantages outweigh the advantages. In addition, the prospect theory by Kahneman and Tversky (1979) assumes the presence of risk factors, which appear and influence an individual's decision under uncertainties. In this work it is argued that risk factors are not the same as perceived disadvantages, but that they could increase the likelihood of rejection, since individuals generally act to avoid risk (Kahneman & Tversky, 1979). An individual will therefore often prefer the less risky option, even if the advantages of the alternative prevail (Yang, Liu, Li, & Yu, 2015).

In view of the current discussion on RDM in higher education (HE), it is essential to examine whether the refusal of the researchers is caused by uncertainty-related risk factors or by a generally low perceived value of RDM. To get to the bottom of the problem, the concept of social exchange theory and the idea of prospect theory were adopted, leading to the following research question: *How do risk determinants and perceived value influence (IS) researchers' decision to comply with new guidelines on RDM?*

Future results and insights of this research will be highly relevant for data and knowledge management executives in HE and librarians, since RDM and data reusability in science are at present an important topic (Link et al., 2017; Ribes & Polk, 2014; Wilms, Stieglitz, Buchholz et al., 2018). Executives, administrators, and developers of HE institutions gain new insights into researchers' behaviour, which is especially important for further implantation strategies, as well as system development.

The remainder of the paper is structured as follows. We first provide the theoretical foundation and derive our research model, including corresponding hypotheses. We then present the research design, followed by the results, discussion and conclusion.

2. Theoretical background

2.1. Research data management

RDM is defined as the active and ongoing management of data "from its entry to the research cycle through to the dissemination and archiving of valuable results" (Whyte & Tedds, 2011) (p. 1). This includes, for instance, long-term storage and accessibility of research data over time (Shreeves & Cragin, 2008), protection of data (Schopfel et al., 2014), the creation of institutional data repositories (Monastersky, 2013), and the exchange of data (Devarakonda, Palanisamy, Green, & Wilson, 2011; Higman & Pinfield, 2015). The DFG for instance, the major research funding institution in Germany, states that 1) primary research data should be stored for at least ten years on suitable memories, 2) data should be described by metadata, and 3) each scientist or academic should make his or her primary research data freely available (if possible) (Deutsche Forschungsgemeinschaft, 2017). In this regard, RDM does affect "any research materials resulting from primary data collection or generation, qualitative or quantitative, or derived from existing sources intended to be analysed in the course of a research project" (Corti, den Eynden, Bishop, & Woollard, 2014, p.viii). Besides raw data, RDM covers any informational data that has been given meaning by way of relational connection, as well as research publications which can be described as a type of stored knowledge (Kuula & Borg, 2008).

2.2. Social exchange theory

Social exchange theory is a socio-psychological approach which defines interpersonal interaction as a process where participants and their partners engage in activities and exchange valuable resources (Chia-An Tsai & Kang, 2019; Homans, 1958; Wang, 2013). One of the key assumptions of the social exchange theory is that individuals use different forms of social interaction which are built upon reciprocal exchanges and which are based on a self-interested evaluation of costs and benefits (Colquitt et al., 2013). Based on an evaluation in which costs and benefits are weighed against each other, the individual will make a decision as to whether or not an interaction takes place (see. Fig. 1). Thus, people will not tend to interact with each other unless they find that the exchange is beneficial for them. Costs, for example, are the time and effort the individual has to invest in the interaction. Benefits, on the other side, include the economic and social rewards the individual expects to gain from the interaction (Wasko & Faraj, 2005).

The social exchange theory has been applied to several contexts related to knowledge management and knowledge sharing (Liang et al., 2008). According to Rode (2016), people are more willing to manage and share their knowledge when costs are low and benefits are high. While this concept alludes to the economic principle of value maximization, there are significant differences: In contrast to economic exchange theory, where the other side of the exchange is the entire market, the exchange in social exchange theory is between human actors (Wang, 2013). The distinction is important, since social exchange mechanisms use social capital as an opportunity to compensate the cost incurred e.g. by possible knowledge senders. The concept of social capital is used to explain knowledge exchange behaviour, and refers to the collective abilities that arise from social networks (Bourdieu, 1977). According to Wang (2013), a social exchange based on social capital can be illustrated, for example, by a situation where an individual A passes his/her experience on to individual B for free in order to gain prestige and reputation.

2.3. Prospect theory

The prospect theory seeks to explain and predict individuals' behaviour, e.g. in a situation where the individual has to decide whether an alternative behaviour is chosen over the current behaviour (status quo). According to the prospect theory, individuals tend to use mental reference points to code the outcome of an action as a gain or loss. For each decision, the individual sets a new mental reference point, which could be described as a mental representation of the status quo. The outcome of this decision is based on the comparison of the reference point and the new alternative (e.g. current behaviour as reference point vs. new behaviour as new alternative).

During the evaluation process, individuals are more sensitive to losses than to gains (H.-W. Kim, Chan, & Gupta, 2007). When the individual needs to decide whether to remain at the reference point or to change to a new alternative, the potential losses compared to the current status quo quickly come to mind. Individuals tend to value losses higher than benefits, leading to the prospect that the sacrifices occurring on a switch from the reference point will hurt more than the expected pleasure (Kahneman & Tversky, 1979). This effect is caused by

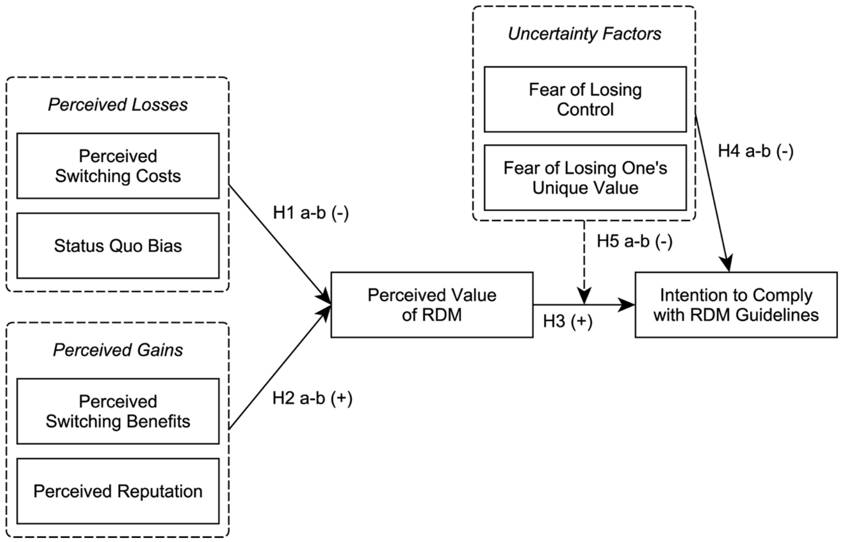

Fig. 2. Hypotheses in the value-based model.

risk aversion which comes up every time that individuals start to evaluate possible risks associated with the new alternative. A change from the current behaviour to a new one causes uncertainties since the individual may be anxious about the possible unknown outcome. According to prospect theory, individuals tend to prefer a certain option even if the evaluation of the alternative is higher (Kahneman & Tversky, 1979). Prospect theory has been conceptualized before in the contexts of IS adoption (Constantiou, 2009; Feng & Yan Tam, 2013; Kim et al., 2007), behavioural actions in online environments (Chiu, Wang, Fang, & Huang, 2014; Kim & Kankanhalli, 2009; Yang et al., 2015), and rational decision making (Afflerbach, 2015; Park & Sung, 2013).

3. Research model development

Drawing on Kahneman and Tversky's (1979) original prospect theory and Homans's (1958) social exchange theory, this section describes the development of the research model. It includes a small number of factors that should account for most of the variance in the intention to comply with research data management guidelines. The model is shown in Fig. 2. All constructs used in this model and cross-loadings are presented in the Appendix.

3.1. Perceived losses

According to social exchange theory, an evaluation takes place after the benefits and costs of an action have been weighed against each other. Previous literature has evaluated such costs which might be incurred on a behavioural change and which need to be overcome in order to change the reference point (Kim & Kankanhalli, 2009; Ranganathan, Seo, & Babad, 2006). Non-monetary costs incurred on a change usually include time, effort, and psychological cost, for example frustration (Bender, 1964; Zeithaml, 1988). As prior research has shown, individuals will justify keeping their current behaviour instead of making the effort it takes to learn a new one (Lending & Straub, 1997). According to rational decision-making principles, costs that are incurred on a behavioural change decrease the perceived value of the change to individuals. Therefore, it is expected that perceived switching costs will decrease the perceived value of RDM. Hence, it can be hypothesized that

H1-a. Perceived Switching Costs have a negative effect on the Perceived Value of RDM.

In line with the prospect theory, the status quo bias (SQB) describes a mental state where a person is strongly bound to his or her usual behaviour, and resists any changes. A person affected by this bias will be more likely to resist any behavioural changes, since dealing with a new situation would affect the status quo (Samuelson & Zeckhauser, 1988). SQB has been identified in different studies in which users had to change their former behaviour (Kim & Kankanhalli, 2009; Polites & Karahanna, 2012). This bias often occurs when users have to evaluate costs, due to the fact that changing the current behaviour means leaving the current reference point and therefore giving up on the status quo. Thus, it is expected that SQB has a strong impact on the relationship between the perceived switching costs and the perceived value. It is therefore hypothesized that

H1-b. Status Quo Bias has a negative effect on the Perceived Value of RDM.

3.2. Perceived gains

Benefits refer to the perceived utility that someone gains when changing from the status quo to a new behaviour (Kim & Kankanhalli, 2009). Within this study, benefits refer to the perceived utility researchers would enjoy due to switching from their current way of managing research data to a new alternative, which fits common norms of adequate RDM. The switch (or change in behaviour) to a new method of data management could result in benefits in the form of performance enhancements, quality enhancements and higher expected effectiveness. We expect that higher switching benefits will increase the perceived value of RDM. We thus present the following hypothesis:

H2-a. Perceived Switching Benefits has a positive effect on Perceived Value of RDM.

To encourage an active knowledge management without giving any rewards is hard to achieve. Knowledge is a laboriously collected repertory of information that no one is willing to offer without any motivation. However, sharing and managing knowledge can have a rewarding structure by showing others the obtained expertise and in doing so, enhancing one's self-confidence (Ba, Stallaert, & Whinston, 2001). There are several studies suggesting that participants offer knowledge to earn peer recognition (Hsu, Ju, Yen, & Chang, 2007) and to improve their status in the community (Marett & Joshi, 2009). This implies that if people notice that knowledge management might affect their reputation in a positive way, they are more inclined to share information (Wasko & Faraj, 2005). Furthermore, a study by Piwowar, Day, and Fridsma (2007) shows that researchers can expect a higher citation rate, going in line with an increased reputation. Therefore, reputation can be seen as an essential motivational factor for knowledge management (Kankanhalli, Tan, & Wei, 2005). Since (research) data management is strongly related to knowledge management, the following hypothesis is suggested:

H2-b. Reputation has a positive effect on the Perceived Value of RDM.

3.3. Perceived value of RDM

Value is defined as a trans-situational goal, which varies in importance and serves as a guiding principle in the life of a person (Schwartz, 1994). According to Gutman (1997), values constitute motivational constructs that directly influence people's behaviour and decision making. According to the value function, based on the prospect theory, perceived value can be defined over perceived gains and losses relative to some natural reference point (Kahneman & Tversky, 1979). Similar to this, the theory of social exchange suggests that the perceived value of an action is calculated by weighing costs and benefits, which are psychological equivalents to losses and gains (Homans, 1958). If the individual evaluates the perceived value of an action as low, the individual develops a greater resistance to change (Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). On the other side, if the value evaluation of an action is high, individuals are less likely to resist the changes (Cao, Duan, & Cadden, 2019; Sirdeshmukh, Singh, & Sabol, 2002). While the relationship between perceived value and intention to comply with RDM guidelines has never been evaluated before, there are various studies which indicate that perceived value has an influence on individuals' intention to change the current behaviour, e.g. in cases of IT adoption (Kim et al., 2007), knowledge transfer (Bagheri, Kusters, & Trienekens, 2019) or consumer decision making (Sweeney, Soutar, & Johnson, 1997). Therefore, perceived value is defined as an indicator which regulates users' behavioural intentions to practise RDM. Thus, it is hypothesized that

H3. Perceived Value has a positive effect on the Intention to Comply with RDM Guidelines.

3.4. Uncertainty factors

Uncertainty factors are defined as emotion-based psychological determinants, "comprising worries regarding a potential threat as yet unidentified or unrealized accompanied by a similar – but attenuated – version of the physiological reaction to fear" (Carleton, Sharpe, & Asmundson, 2007, p.1). In contrast to advantages and disadvantages, uncertainty factors represent emotionally based concerns about future injustice and do not directly influence the value of an action directly (Lagrange, Ferraro, & Supancic, 1992; Rountree & Land, 1996). The difference between uncertainty factors and perceived pain and gain factors can be illustrated by an example from air traffic: Although passengers are aware that flying is cost-efficient and the risk of crashing is low, they may have fear of entering a plane, which ultimately prevents them from flying. This fear is not a disadvantage of air traffic, but a personal fear deeply rooted in the personality of the passenger.

The same phenomenon also applies to the concept of RDM: While the general concept can be evaluated as valuable (if the gains outweigh the pains), uncertainty factors might prevent the researcher from practicing RDM. Uncertainty can be provoked through the perception of risky situations or actions (Featherman, 2001) and it is negatively associated with usage behaviour (Featherman & Pavlou, 2003; Jarvenpaa & Staples, 2000). Therefore, uncertainty during decision making could lead insecure people to remain in their status quo (Ortoleva, 2010). Since control over sensitive data or information security is a major concern of individuals, it deters them from uploading their data to an online repository (Horvath & Rajeev, 2015; Li et al., 2019; Shaikh & Sasikumar, 2012). Based on the findings of Feijen (2011), researchers think that they have more control if they tend to manage their research data locally. Hence, it is hypothesized that there is a direct relationship between perceived risk of losing control and the actual intention to conduct RDM. Thus, it is hypothesized that

H4-a. Fear of Losing Control has a negative effect on the Intention to Comply with RDM Guidelines.

As studies have shown, another barrier to knowledge management is a potential loss of knowledge power (Huang, Davison, & Davison, 2008). When losing power, individuals may lose their value by giving up their uniqueness (Gray, 2001). Offering knowledge or data to others might cause the source to lose its unique value relative to what others know (Renzl, 2008), especially when others benefit from the results (Wasko & Faraj, 2005). If individuals fear losing in a cooperative relationship based on open access, they reject the whole concept. The fear of losing one's unique value serves as a determining factor in the decision process, since it reflects uncertainties that researchers fear by switching from the status quo. Thus, it is hypothesized that

H4-b. Fear of Losing One's Unique Value has a negative effect on the Intention to Comply with RDM Guidelines.

As a basic principle of prospect theory, it is expected that after evaluating the potential losses and gains, it is possible that people choose the less beneficial alternative because it is associated with less uncertainty. As a result, although we expect users who perceive RDM as valuable to intend to comply with RDM guidelines, this relationship might be affected by the level of uncertainty. Some researchers might fear a loss of control over their data after sharing it publicly, and perceive a diffuse threat that others could misuse their data. As a consequence, they might be less influenced by a positive net evaluation of the benefits and drawbacks to follow the new guidelines. This expectation leads to the following hypothesis.

H5-a. Fear of Losing Control negatively moderates the effect of Perceived Value of RDM on the Intention to Comply with RDM Guidelines.

Equally, researchers who fear losing their unique value if they share their data might be affected by this in how their appraisal of the advantages and disadvantages of the new guidelines translates into a willingness to switch. While the concept stems from management research (Renzl, 2008), a researcher's unique value in an academic setting is their knowledge advantage that contributes to their standing in their respective research community.

H5-b. Fear of Losing One's Unique Value negatively moderates the effect of Perceived Value of RDM on the Intention to Comply with RDM Guidelines.

4. Research design

This work aimed to evaluate how the intention to comply with research data management regulations (RDM guidelines) is influenced. Before measuring researchers' intentions, it was ensured that all of the participants had a common understanding of RDM guidelines. Since data may be managed differently in different academic areas and institutions due to varying regulations, legal restrictions, or data management culture, a few requirements for the experimental approach were set up:

First, researchers of a specific scientific discipline were recruited. The Information Systems (IS) discipline is known as a "data poor field" with inadequate data preservation and reuse practices, and with relatively little advanced data instrumentation (Lyytinen, 2009). Furthermore, previous IS literature has continuously called for adequate data management policies in this field (Avital et al., 2007; Link et al., 2017; Lyytinen, 2009; Wilms, Stieglitz, Buchholz et al., 2018). Since IS is known as an IT-related discipline in which RDM has become an important issue during the last decade (Link et al., 2017), researchers from this field of research were selected for the study. Second, since IS researchers can be distinguished by their geographic locale (Avgerou, Siemer, & Bjørn-Andersen, 1999), the questionnaire aimed to capture only data from IS academics in Germany. The Deutsche Forschungsgemeinschaft (DFG) is one of the primary research funding institutions for IS research in Germany, and offers representative guidelines on RDM (Wilms, Meske, Stieglitz, Rudolph, & Vogl, 2016) (see Appendix B). Third, in order to ensure that all of the participants were aware not only of the DFG as a third-party funding institution, but also of its guidelines on RDM, the survey started by 1) asking the participants if they knew about DFG, and 2) briefing the participants about the guidelines in detail.

To assess model constructs, a quantitative online questionnaire was developed and pretested. All item instruments within this study were adopted or modified from previously validated instruments in order to ensure adequate measurements. All of the borrowed measurements were originally published in the English language. To avoid translation biases, the questionnaire was kept in English as well. All items were measured on a 5-point Likert scale ("Strongly Agree" – "Strongly Disagree"). To test the hypotheses, the following constructs were used: To measure *perceived value*, we modified the 3-item scale from Kim and Kankanhalli (2009). *Perceived Switching Benefits* and *Perceived Switching Costs* were also adopted from Kim and Kankanhalli (2009). *Intention to Comply with RDM Guidelines* was measured by using the modified 3-item scale of switching intention by Bhattacherjee and Park (2014). *Status Quo Bias* was measured using original scales from Polites and Karahanna (2012). *Reputation* was measured by using the modified scale of Chang and Chuang (2011). *Fear of losing one's unique value* was conceptualized by using the scale of Wang and Chan (2012). We measured the construct of fear of losing *one's unique value* with the modified scale of Renzl (2008) and the construct *fear of losing control* with the modified scale from Ernst (2015).

First, the adopted and modified instruments were reviewed and discussed by six reviewers, resulting in minor changes in wording. Second, construct validity and comprehensibility were ensured using five raters and an open sorting procedure (Moore & Benbasat, 1991). Third, a pilot study with 20 participants was set up to receive feedback on item composition, wording and length. The participants were asked to give feedback on the instructions, survey length and other issues they experienced. Afterwards, the instruments were shortened and refined. The final constructs and items are shown in Appendix A. The survey was conducted online between March and June 2017. To reach a greater number of participants, a survey link was spread among a mailing list for the German community of Information Systems academics (at that time we reached 1124 people). In a second round, 301 IS researchers from Germany were contacted directly by email and asked to participate.

5. Results

The research model was transferred into a structural equation model (SEM) for validation (Chin, 1998). Due to the sample size (less than 500) and since the sample does not fully follow a multivariate normal distribution, which is required by covariance-based SEM (CB SEM) methods, the partial least squares method offers a suitable alternative for SEM showing a greater robustness (Ringle, Wende, & Becker, 2014). PLS is a composite-based approach to SEM, which aims at maximizing the explained variance of dependent constructs in the path model (e.g. Hair, Hult, Ringle, & Sarstedt, 2014). All the hypothesized constructs were modelled as reflective measures of their respective indicators.

5.1. Descriptive data

Overall, 111 completed responses were collected (response rate: 7.8 %). Out of all the collected datasets, 11 participants were excluded since they indicated 1) that they were not responsible for managing their own research data or 2) that they already followed strict data management guidelines. Furthermore, we excluded those participants with suspicious completion times (less than 5 min), which left us with a total of 96 adequate data points. The size of the dataset is suitable for the PLS-based approach since it is higher than the minimum recommended by Hair et al. (2014), which is calculated as the number of indicators multiplied by ten. In terms of gender distribution, there was a majority of male participants, since only 33 of the participants were female (34 %). The average age was 37. Thirty-two of the participants were employed as full university professors (33 %), whereas 26 were working as post-docs, assistant professors or senior lecturers (27.1 %). Thirty-seven of the participants stated that they worked as doctoral candidates (38.5 %). All of the participants indicated that they had full authority over their research data. 81.3 % of the researchers indicated that more than three-quarters (> 75 %) of their research data are generated in digital formats, while 31.3 % said that they had already experienced data loss.

According to our findings, only 10.4 % of the participants stated that they are aware of data management standards such as institutional guidelines (e.g. documentation standards). The majority of researchers, namely 53.1 %, use self-developed procedures for documentation. Furthermore, more than one quarter of the university employees (27.1 %) do not use data management standards at all. 9.4 % of the participants indicated that they do not know about data management standards. To ensure that the sample is not distorted by cultural biases such as age, gender and job position, we tested the influence of these factors on the measured variables used in the model. We did not identify any significant influences here.

5.2. Measurement model

The reflective measurement model was assessed by estimating reliability, as well as convergent and discriminant validity (see Table 1). Reliability was assessed since the composite reliability (CR) of all constructs was above the threshold of 0.70 (Fornell & Larcker, 1981). Convergent validity was assumed, since the average variance extracted (AVE) for each construct exceeds the threshold of 0.50 (Fornell & Larcker, 1981). Discriminant validity is tested by comparing the square root of AVE for each construct with the bivariate correlations of each measured construct (Fornell & Larcker, 1981). Discriminant validity

Table 1
Reliability and Validity Measurements. CR = composite reliability, AVE = average variance extracted. Bold numbers on the diagonal are the square root of the AVE.

Variables	CR	AVE	1	2	3	4	5	6	7	8
(1) Fear of losing control	.91	.77	**.88**							
(2) Intention to comply	.96	.89	−.32	**.94**						
(3) Reputation	.95	.82	−.16	.39	**.91**					
(4) Perceived switching benefit	.94	.83	−.09	.39	.33	**.91**				
(5) Perceived switching cost	.80	.57	.49	−.33	−.33	−.13	**.75**			
(6) Unique value	.89	.73	.61	−.19	−.18	−.15	.49	**.85**		
(7) Value of RDM	.93	.81	−.33	.66	.48	.64	−.40	−.30	**.90**	
(8) Status quo	.87	.69	.01	−.06	.16	.17	.06	.07	.08	**.83**

Table 2
Main effects model.

Predictor	Standardized Beta	S.E.	t-value	p-value
Fear of losing control	−.18	.10	1.80	.037
Perceived reputation	.23	.09	2.65	.004
Perceived switching benefit	.53	.06	8.43	.000
Perceived switching cost	−.25	.09	2.86	.002
Fear of losing one's unique value	.11	.10	1.03	.152
Perceived value of RDM	.63	.07	8.61	.000
Status quo bias	−.04	.07	0.47	.319

Table 3
Moderating effects model.

Predictor	Standardized Beta	S.E.	t-value	p-value
Fear of losing control	−.22	.11	2.05	.021
Perceived reputation	.23	.09	2.54	.006
Perceived switching benefit	.53	.07	8.06	.000
Perceived switching cost	−.25	.08	3.06	.001
Fear of losing one's unique value	.12	.11	1.08	.140
Perceived value of RDM	.61	.08	7.74	.000
Status quo bias	−.04	.07	0.47	.319
Fear of losing Control * Value of RDM	−.12	.08	1.55	.061
Unique Value * Value of RDM	.09	.07	1.24	.107

can be assumed when the square root of AVE is greater than any inter-factor correlation. The scores are summarized in Table 2. Before the testing of the hypotheses, it was ensured that the measurement was not affected by the common method bias (CMB). To alleviate concerns about CMB, Harman's one-factor test was conducted to identify common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The single factors calculated accounted for 31.04 % of the variance in the model. Additionally, the factors did not account for most of the covariance. In addition to Harman's one-factor test, multi-collinearity was tested using the inner variance inflations (VIF), resulting in values between 1.00 and 3.00, which is lower than the suggested maximum values of 3.30 (Kock, 2015). Therefore, the data set was not affected by the CMB.

5.3. Structural model

Fig. 3 shows the results of the structural path analysis. All of the paths related to prospect theory were significant, with a p value less than 0.05. The significance of all of the paths was assessed by 500 bootstrap runs. All of the correlations are listed in Appendix A.

Overall, the developed main model could explain nearly 46 % ($R^2 = 0.455$, adjusted $R^2 = 0.437$) of the variance in the intention to comply with RDM guidelines. Additionally, 55 % ($R^2 = 0.546$, adjusted $R^2 = 0.526$) of the variance in the perceived value of RDM could be explained by our model (see Fig. 3). Table 2 summarizes the results of our survey. Overall, five out of seven hypotheses were confirmed.

To assess the statistical power of our data, we analysed the effect size by calculating Cohen's f^2. Cohen (1988) suggested the following criteria for interpreting effect size: (1) for small effect size, $.02 < f^2 \leq .15$; (2) for medium effect size, $.15 < f^2 \leq .35$; and (3) for large effect size, $f^2 > .35$. The effect size of Perceived Value ($f^2 = .64$) was large and contributed significantly to the R^2 of further Intention. The effect size of Switching Benefits was large ($f^2 = .55$), while the effect size of Perceived Switching Cost was small ($f^2 = .12$). Reputation showed a small effect size ($f^2 = .09$), while Status Quo Bias had no significant impact on Perceived Value ($f^2 = .003$). The uncertainty factors Fear of losing Control ($f^2 = .04$) and Fear of losing one's unique value ($f^2 = .013$) also showed small effects sizes. In addition, the predictive relevance was analysed by application of the Stone-Geisser test (Q^2), which indicates how well the data can be reproduced by the PLS model. The Q^2 values for perceived value ($Q^2 = .41$) and Intention to conduct RDM is ($Q^2 = .37$) is positive, indicating a high level of predictive relevance.

Our moderating effects model increased the variance explained (R^2) in Intention to conduct RDM from 46 % in the main effects model to 47 % in the moderating effects model (see Table 3). Cohen's f^2 value was $f^2 = 0.02$ for Fear of losing control, and $f^2 = 0.012$ for Unique value, suggesting that the moderating effects in our study had only a slight effect.

6. Discussion

The research model in this study was built on social exchange theory (Homans, 1958) and prospect theory (Kahneman & Tversky, 1979). Based on social exchange theory, value was defined as the combination of various costs and benefits perceived by the researchers if they were asked to practise defined standards of RDM. This principle was adopted from other research on knowledge management, where the intention of managing knowledge was related to individuals' evaluation of the action.

As we expected based on social exchange theory, the results indicate that the perceived value of RDM is influenced both by negative

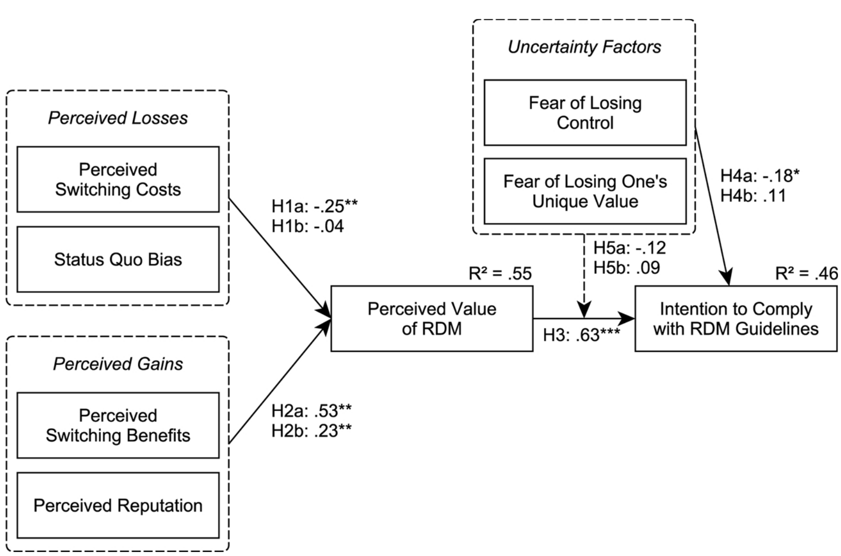

Fig. 3. Research model (n = 96). *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001.

elements such as perceived switching costs and by positive, non-monetary aspects such as reputation and perceived switching benefits in context of workload.

While several studies indicate that defined RDM standards create too high a workload for researchers and therefore hinder researchers from practicing RDM, our results paint a different picture. While the threat of an increased workload has a moderate negative impact on the evaluation process (H1a), H2a shows that researchers are strongly influenced by the potential advantages of following a well-defined and guided knowledge management process. This is an interesting finding, because it conflicts with the assumption that an increased workload is the reason researchers reject RDM (e.g. Feijen, 2011, Bauer et al., 2015). One possible explanation for this finding is that the sample primarily consists of technically experienced researchers. They have better access to technologies such as cloud computing and a greater understanding of data protection (Wilms, Brenger, López, & Rehwald, 2018; Wilms, Stieglitz, Buchholz et al., 2018; Wilms, Stieglitz, & Müller, 2018; Meske, Wilms, & Stieglitz, 2019). Moreover, universities have increasingly invested in data storage systems in recent years and have made researchers sensitive to these issues (Vogl et al., 2016; Wilms et al., 2016).

Another interesting finding is that the status quo bias did not seem to have any effect (H1b). A bias in favour of the status quo is often a strong driver of why people are reluctant to change their behaviour. Here again, the reason for this result might be explained by institutions' efforts to educate researchers. There is currently a massive push for digitization in universities (Stieglitz, Meske, Rudolph, & Vogl, 2014). As Wilms, Stieglitz, Müller et al. (2018) and Stieglitz, Wilms, Rudolph, and Vogl (2018) could show, researchers' interest in switching from analogue workarounds to cloud-based solutions has increased.

As a further motivational factor, we were able to show that the expectation of an increased reputation is a driver in the evaluation of RDM (H2b). The result confirms earlier research findings that reputation is one of the main characteristics (Kim & Zhang, 2015; Piwowar and Vision, 2013).

In summary, these results show that during the evaluation process of the RDM guidelines, the advantages of structured data management clearly outweigh the disadvantages. Hence, the results indicate that researchers see a high benefit in the *preservation and disclosure of research results*. Isolated from other effects such as the presence of uncertainty factors, these findings are quite important, since other descriptive research assumed that disadvantages such as increased time and effort outweighed advantages (e.g. Borgman, 2012; Feijen, 2011). A possible explanation discussed below is the understanding of research data as symbolic capital. Research data are often regarded as a researcher's most important resource, which can be used to gain reputation and recognition (Borgman, 2012; Piwowar et al., 2007). According to the definition of Bourdieu, symbolic capital refers to the opportunities that lead to gaining and maintaining social recognition and prestige (Bourdieu, 2015). As a sign of social recognition and power, symbolic capital bestows prestige, reputation, and positions. From this point of view, the presence and the visibility of high-quality research data can be used to successfully increase an individual's status in the research community. Thus, researchers who collected good and valuable research data and who are willing to share these data command a high amount of symbolic capital and therefore increase their standing in their community. Although previous research assumed that researchers expect a benefit for the community rather than personal benefits from managing and offering research data (e.g. Piwowar et al., 2007), this works' results indicate that researchers are indeed aware of personal benefits.

But why is the acceptance of RDM standards still so low among scientific communities? Why did nearly 90 % of the participants indicate that they do not use institutional or national standards? To answer that question, we need to take a deeper look at the results and focus on the presence of uncertainty factors. Based on prospect theory, it is expected that the presence of uncertainty factors impacts the intention to conduct RDM both directly and by moderating the effect of perceived value of RDM on the intention to actually comply with RDM guidelines. In this regard, it was expected that even if the benefits outweigh the cost and the evaluation is high, uncertainty factors could impact the final decision-making and cause the individual to pick the less beneficial alternative. The uncertainty factor *loss of control* indeed appears to be a hindering factor for researchers to follow RDM guidelines (H4a). Since this study focusses on the RDM guidelines in general, including all recommendations such as preservation and disclosure of research results, we can only assume that the fear of losing control refers to the recommendation to give other interested parties access to the research data. This is also supported by the results from previous studies, where researchers indicated that they could develop negative feelings when disclosing their research data (Fecher, Friesike, & Hebing, 2015; Feijen, 2011; Kim & Zhang, 2015; Piwowar, 2011). The unwillingness to share resources in parallel work situations is deeply rooted in the human mindset (Hamann, Warneken, Greenberg, & Tomasello, 2011). From the psychological findings of Hamann, Warneken, and Tomasello (2012), it can be expected that this reluctance will diminish if researchers increasingly work together towards a joint goal. A look at other research disciplines shows that such joint goals could be manifested, for example, through the establishment of knowledge and data repositories (e.g. Arend et al., 2014; Príncipe, Rettberg, Rodrigues, & Elbæk, 2014).

In contrast, the uncertainty factor *fear of losing one's unique value* has no significant effect on the intention to conduct RDM (H4b). This is a rather surprising finding, since it disagrees with the assumptions of Renzl (2008), who assumed that offering knowledge or data to others might cause the source to lose its unique value relative to what others know. Yet, in the work of Renzl (2008) managers were surveyed, not researchers, who usually compete with others on an economic basis. Albeit studies show that the sharing of ideas and innovations holds a positive effect for entrepreneurs, this fear is still present in managers.

Neither does the fear of losing one's unique value have an effect on the relationship between perceived value of RDM and the intention to comply with RDM guidelines (H5b). Since the fear of losing one's unique value also did not affect this intention directly, it can be concluded that unlike in a business context, the academic setting does not appear to push researchers to avoid a beneficial decision due to a fear of losing their unique value. Another possible explanation might be that other research investigations focused on multiple research areas, including e.g. natural sciences (e.g. biology), engineering or medicine. As indicated by Bauer et al. (2015), those research areas are characterized by strong competitive pressures. Adverse factors such as the fear of losing one's unique value might be more relevant in these specific research areas than in IS.

While the fear of a loss of control directly influences the intention to comply negatively, it does not change the effect of perceived value of RDM on this intention (H5a). There was thus no evidence of uncertainty factors moderating the relationship between the perceived value of RDM and the intention to comply with RDM guidelines. While it might be dangerous to share ideas and findings too early in a business context, the researchers surveyed in this study are less critical concerning possible disadvantages. Still, in academic research, there is also a risk of shared ideas being published by competitors, but that strongly differs from discipline to discipline and between different communities (Wilms, Brenger et al., 2018; Wilms, Stieglitz, Buchholz et al., 2018; Wilms, Stieglitz, Müller et al., 2018). In some disciplines, especially in the humanities, researchers are more reluctant to share their data than in the natural sciences, where there is a huge pressure to share data before studies are published in order to 'reserve' the specific field of research (Wilms, Brenger et al., 2018). The fear of shared data published by competitors is also rather restrained in computer science.

6.1. Theoretical contributions

The main theoretical contribution of this research is the development of the new model, which offers a novel perspective on researchers' intentions to comply with RDM guidelines. In this model, the entire RDM integration process is viewed in the context of social exchanges. This work's value-based perspective helps to understand the potential pains and gains researchers face when they have to decide whether to perform RDM or not. While previous research on RDM integration was not able to determine the relevance of individual supporting and hindering factors for RDM integration, the model developed in this work identifies of several important determinants in this process. The model in this work includes a small number of factors that account for a substantial portion of the variance in the intention to comply with research data management guidelines, and the value-based model offers a theory-based framework for further investigations in the context of (research) data and knowledge management. By introducing the prospect theory as a novel explanatory component for the negative outcome of decision-making processes, future research in the field can benefit as much as ongoing research in the field of RDM integration.

6.2. Implications for practice

The results paint an accurate picture of the current state of acceptance of RDM policies in scientific communities and explain which factors may determine whether RDM will be practiced by researchers in the future. An overview of the current status quo is very important at this point in time, as a lot of work and effort has been invested by universities in recent years in preparing satisfactory guidelines for RDM.

Overall, they are highly relevant for universities and research communities currently implementing RDM policies and concepts, for researchers themselves who want to establish the topic in their communities, for knowledge management researchers, who can observe such processes in economic contexts, and for managers who want to establish new structures and guidelines in their companies. Research institutions have new grounds to build novel RDM implementation strategies, and the results of our study are highly relevant for the ongoing discussion around the introduction of mandatory standards.

The key aspects that are relevant for these practitioners are the following. In the context of RDM, the requirement to comply with possible guidelines is clearly not sufficient to convince researchers to change their current inadequate data management strategies. Overall researchers see the added value in a potential change of behaviour, in favour of conducting better RDM, and even evaluate it positively. However, a large part of respondents claimed not to practise RDM. The reasons for this behaviour can be partly explained by the presence of uncertainty factors, especially the fear of losing control. In order to convince researchers to conduct RDM in the long term, it is not enough to simply discuss its advantages. A behavioural change can take place if the uncertainties are also removed. Here the feeling of control is an important factor for the knowledge author.

A perceived increased workload may contribute to the fact that a behavioural change is regarded as negative by the researchers. It is therefore important to convince them that no additional technical effort is required. Current technical developments in data management systems such as cloud computing support a possible introduction process of RDM. It is important to make such technologies available to researchers and to regulate the general conditions such as data security and data protection.

The fear of losing control arises when researchers think that they are "forced" to share their data without knowing who will use the data and how. Thus, the level of uncertainty must be reduced by giving researchers back the perceived control over their research data. Research infrastructures need to interlink submissions, reveal joint goals between researchers and focus on concepts of group-building processes (e.g. Pries-Heje & Pries-Heje, 2011), to raise the acceptance of data sharing.

Researchers must have the opportunity to inform themselves about their rights in case of data abuse. Uncertainties are not only caused by strict data sharing policies – they occur due to uncertainties in regard to ethical restrictions and national data protection laws (Verbaan & Cox, 2014). Since universities generally do not have the capacity to evaluate research projects in detail and provide feedback, strategies must be developed to inform researchers efficiently and without much effort about their basic rights.

The results are also important for knowledge management practitioners, as they show how individuals evaluate and protect knowledge as a resource, even in ecosystems that are mainly driven by nonmonetary incentives. The results from this study partly contradict research results from the research of knowledge management in business contexts. Results from a business context cannot be transferred directly to KM in a research context. Unlike in the business context, knowledge in academic research is not directly linked to monetary benefits. Academia, as a government-subsidized sector that is meant to accumulate knowledge to benefit the public good, is thus an interesting contrast to such settings. For a business, the protection or the patenting of exclusive knowledge provides a monetary advantage which possibly protects a monopoly, but in research, knowledge serves more as a status symbol.

6.3. Limitations and future research direction

The participants in this study were IS researchers in Germany and they only represent a small group within the IS discipline. While it could be argued that studies using small sample sizes are not meant to quantify general tendencies within a population, the data set is large enough to document the existence of an effect.

There is also a subtle difference between researchers managing their research data for their own benefit, and sharing it widely for the benefit of others. The RDM guidelines that we used deal with both, but there might be subtle differences in intention to comply when guidelines are considered that primarily focus on one aspect over the other.

To validate the findings in this work, future research is needed to investigate a broader range of samples. Future investigations need to research requirements for technical solutions on an international level. Especially requirements such as open access might be different in countries which are more collectivistic, and countries where data protection laws are not as strict as in Germany might have a different understanding of data protection and security. Specific German legal frameworks that may differ from those in other countries, as well as the organizational culture at German universities, may influence the generalizability of the results. Individual differences and national cultures might affect how RDM unfolds under differences along this dimension. The questionnaire focused on participants who had a common knowledge of RDM and of guidelines related to the DFG. These guidelines are related to the German research community but do not completely fit the guidelines of other international funding institutions. Even today, there is no common definition or standard for how research data should be managed equally.

Our model focuses on the effects of perceived switching benefits, costs and uncertainty on intention to comply with guidelines. The specific reasons that lead researchers to perceive such benefits and costs in the first place are outside the scope of this study. Future research could extend the model by examining these factors. Recent studies also point out that, in addition to fear of losing control, fear of job disadvantages (Kim & Zang, 2015) or fear of competition (Bauer et al., 2015) increase uncertainty during the decision-making process. Besides additional uncertainty factors, we expect personal factors and experience to have a significant impact on the willingness to change one's behaviour. While the results of this research are limited at this point, we call for future research investigations to develop suitable measuring instruments and to examine the influences of these and other possible impact factors. The model presented in this paper provides a suitable starting point.

Finally, the goal of our research was to examine the factors that contribute to the intention to follow new RDM guidelines. However, a researcher who has formed the intention to follow new RDM guidelines might still be prevented from actually doing so, for example by time constraints. These are outside the scope of our model but could be targeted with future research.

7. Conclusion

The amount of digital data is growing at an ever increasing pace. As researchers collect more and more data, the challenges associated with managing the data also grow. In this context we conducted a quantitative study of the factors affecting researcher's intention to comply with guidelines on handling research data. A number of key points emerge from this research. Overall acceptance of RDM policies is low. To encourage the adoption of new standards, it is crucial to clearly explain their benefits to researchers so they perceive RDM as valuable. However, a simple weighing up of benefits and drawbacks, as suggested by social exchange theory, is not enough to explain the intention to follow RDM guidelines. Following prospect theory, uncertainty can prevent people from choosing an option even if they evaluate it as more beneficial. In terms of RDM guidelines, this uncertainty consists primarily of the risk of losing control over one's data. The resulting model combines both theories to explain why researchers form the intention to follow RDM guidelines. It can serve as a foundation for future research in this area.

Funding

This research was not funded by any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Konstantin Wilms: Conceptualization, Methodology, Investigation, Writing - original draft. **Stefan Stieglitz:** Writing - review & editing, Supervision. **Björn Ross:** Writing - review & editing, Supervision. **Christian Meske:** Writing - review & editing.

Appendix A

Table A

#	Measurement Items	Source
FEAR OF LOSING ONE'S UNIQUE VALUE (Mean: 2.58; SD: 1.04)		
UV1	I don't gain anything if I share my research data.	Modified from Renzl (2008)
UV2	If I share my research data, I will lose my knowledge advantage.	
UV3	Sharing research data means losing power.	
FEAR OF LOSING CONTROL (Mean: 2.88; SD: 1.02)		
LC1	The new way of managing research data leads to a loss of control over my work.	Modified from Ernst (2015)
LC2	The new way of managing research data allows others to misuse my research data.	
LC3	Overall, I see a threat to my work if I have to conduct the new way of managing research data.	
REPUTATION (Mean: 2.65; SD: 0.95)		
RP1	I earn respect from others by conducting the new way of managing research data in the scientific community.	Modified from Chang and Chuang (2011)
RP2	I feel that conducting the new way of managing research data improves my status in the scientific community.	
RP3	Conducting the new way of managing research data in the scientific community can enhance my reputation in my professional field.	
RP4	I can earn some feedback or rewards through conducting the new way of managing research data that represents my reputation and status in the scientific community.	
PERCEIVED VALUE OF RDM (Mean: 2.66; SD: 0.82)		
VA1	Considering the time and effort that I have to spend, the change to the new way of managing research data is worthwhile.	Modified from Kim and Kankanhalli (2009)
VA2	Considering the loss that I incur, the change to the new way of managing research data is of good value.	
VA3	Considering the hassle that I have to experience, the change to the new way of managing research data is beneficial to me.	
INTENTION TO COMPLY WITH RDM GUIDELINES (Mean: 2.84; SD: 1.03)		
IC1	I intend to increase the new way of managing research data in the foreseeable future.	Modified from Bhattacherjee and Park (2014)
IC2	I intend to invest my time and effort in the new way of managing research data.	
IC3	I intend to switch from my current way of managing research data to the new way of managing research data.	
PERCEIVED SWITCHING COST (Mean: 3.10; SD: 0.82)		
SC1	It would take a lot of time and effort to switch to the new way of managing research data.	Adopted from Kim and Kankanhalli (2009)
SC2	Switching to the new way of managing research data could result in unexpected hassle.	
SC3	I would lose a lot in my work if I were to switch to the new way of managing research data.	
PERCEIVED SWITCHING BENEFITS (Mean: 2.34; SD: 0.95)		
SB1	Changing to the new way of managing research data would enhance my effectiveness on the job more than working in the current way.	Adopted from Kim and Kankanhalli (2009)
SB2	Changing to the new way of managing research data would enable me to accomplish relevant tasks more quickly than working in the current way.	
SB3	Changing to the new way of managing research data would increase my productivity more than working in the current way.	
STATUS QUO BIAS (Mean: 2.73; SD: 0.93)		
I will continue using my current method for managing research data…		
SQ1	…even though I know it is not the best way of doing things.	Adopted from Polites and Karahanna (2012)
SQ2	…even though I know it is not the most efficient way of doing things.	
SQ3	…even though I know it is not the most effective way to do things.	

Table B

	LC	IC	RP	SB	SC	UV	VA	SQ
LC1	**0.905**	−0.322	−0.157	−0.045	0.431	0.548	−0.285	−0.011
LC2	**0.865**	−0.263	−0.053	−0.068	0.402	0.524	−0.236	−0.007
LC3	**0.853**	−0.234	−0.210	−0.128	0.472	0.522	−0.340	0.053
IC	−0.303	**0.936**	0.339	0.327	−0.279	−0.160	0.583	−0.066
IC	−0.289	**0.968**	0.381	0.365	−0.289	−0.191	0.622	−0.032
IC	−0.305	**0.925**	0.375	0.399	−0.351	−0.184	0.659	−0.057
RP1	−0.159	0.407	**0.910**	0.351	−0.214	−0.171	0.468	0.180
RP2	−0.116	0.316	**0.936**	0.283	−0.366	−0.160	0.446	0.122
RP3	−0.164	0.273	**0.892**	0.198	−0.375	−0.125	0.358	0.136
RP4	−0.137	0.391	**0.886**	0.334	−0.255	−0.176	0.459	0.122
SB1	−0.066	0.332	0.289	**0.900**	−0.163	−0.162	0.604	0.151
SB2	−0.114	0.364	0.326	**0.895**	−0.100	−0.102	0.558	0.209
SB3	−0.059	0.363	0.285	**0.944**	−0.099	−0.140	0.576	0.107
SC1	0.241	−0.199	−0.278	−0.197	**0.782**	0.424	−0.336	−0.070
SC2	0.470	−0.296	−0.308	−0.156	**0.838**	0.342	−0.346	0.153
SC3	0.472	−0.263	−0.100	0.173	**0.626**	0.377	−0.182	0.045
UV1	0.449	−0.196	−0.246	−0.268	0.462	**0.841**	−0.329	0.016
UV2	0.529	−0.126	−0.089	−0.035	0.426	**0.888**	−0.177	0.071
UV3	0.596	−0.145	−0.073	−0.014	0.359	**0.832**	−0.218	0.111
VA1	−0.304	0.540	0.432	0.582	−0.322	−0.263	**0.919**	0.126
VA2	−0.346	0.584	0.433	0.548	−0.403	−0.316	**0.870**	0.059
VA3	−0.234	0.654	0.439	0.588	−0.352	−0.228	**0.916**	0.028
SQ1	0.120	−0.105	0.063	0.016	0.136	0.091	−0.020	**0.690**
SQ2	0.041	−0.063	0.153	0.142	0.085	0.076	0.058	**0.979**
SQ3	0.050	−0.137	0.015	0.068	0.065	0.107	0.008	**0.791**

Appendix B

Short version of the data management policies of the DFG. The full text can be accessed here: http://www.dfg.de/download/pdf/foerderung/antragstellung/forschungsdaten/guidelines_research_data.pdf (last accessed on 22 June 2020)

- A discipline-specific organizational concept that regulates effective and sustainable storage of the data is to be defined.
- The data are described by metadata.
- If possible, each scientist or academic makes his or her primary research data freely available on a transregional level.
- The data are quality-controlled.
- The data are personally labelled and are stored under the name of the researcher.
- The research data are stored within the framework of defined standards.

References

Afflerbach, P. (2015). The business value of IT in light of prospect theory: A new explanation for IT paradoxes. *Business & Information Systems Engineering, 57*(5), 299–310. https://doi.org/10.1007/s12599-015-0400-6.

Ahmadi, N. A., Jano, Z., & Khamis, N. (2016). Analyzing crucial elements of research data management policy. *International Business Management, 10*(17), 3847–3852. https://doi.org/10.36478/ibm.2016.3847.3852.

Arend, D., Lange, M., Chen, J., Colmsee, C., Flemming, S., & Hecht, D. (2014). E!DAL - a framework to store, share and publish research data. *BMC Bioinformatics, 15*(1), 214–224. https://doi.org/10.1186/1471-2105-15-214.

Avgerou, C., Siemer, J., & Bjørn-Andersen, N. (1999). The academic field of information systems in Europe. *European Journal of Information Systems, 8*(2), 136–153. https://doi.org/10.1057/palgrave.ejis.3000319.

Avital, M., Sawyer, S., State, P., Kraemer, K., Sambamurthy, V., & Lyytinen, K. (2007). Data rich and data poor scholarship: Where does IS research stand? *ICIS 2007 Proceedings,* 101.

Ba, S., Stallaert, J., & Whinston, A. B. (2001). Research commentary: Introducing a third dimension in information systems design—The case for incentive alignment. *Information Systems Research, 12*(3), 225–239.

Bagheri, S., Kusters, R. J., & Trienekens, J. J. M. (2019). Customer knowledge transfer challenges in a co-creation value network: Toward a reference model. *International Journal of Information Management, 47*, 198–214. https://doi.org/10.1016/j.ijinfomgt.2018.12.019.

Bauer, B., Ferus, A., Gorraiz, J., Gründhammer, V., Gumpenberger, C., Maly, N., ... Steineder, C. (2015). *Forschende und ihre Daten. Ergebnisse einer österreichweiten Befragung - Report 2015*https://doi.org/10.5281/zenodo.32043.

Bender, W. C. (1964). Consumer purchase costs-do retailers recognize them? *Journal of Retailing, 40*(1), 1–8.

Bhattacherjee, A., & Park, S. C. (2014). Why end-users move to the cloud: A migration-theoretic analysis. *European Journal of Information Systems, 23*(3), 357–372. https://doi.org/10.1057/ejis.2013.1.

Blumenthal, D. (2017). Data withholding in the age of digital health. *The Milbank Quarterly, 95*(1), 15–18. https://doi.org/10.1111/1468-0009.12239.

Borgman, C. L. (2012). The conundrum of sharing research data. *Journal of the American Society for Information Science and Technology, 63*(6), 1059–1078. https://doi.org/10.1002/asi.

Bourdieu, P. (1977). *Outline of a theory of practice.* Cambridge UK: Cambridge University Press Castronova E.

Bourdieu, P. (2015). *Distinction: A social critique of the judgement of taste. Sociological perspectives on sport: The games outside the games*61–68. https://doi.org/10.4324/9781315870854.

Cao, G., Duan, Y., & Cadden, T. (2019). The link between information processing capability and competitive advantage mediated through decision-making effectiveness. *International Journal of Information Management, 44*, 121–131. https://doi.org/10.1016/j.ijinfomgt.2018.10.003.

Carleton, R. N., Sharpe, D., & Asmundson, G. J. G. (2007). Anxiety sensitivity and intolerance of uncertainty: Requisites of the fundamental fears? *Behaviour Research and Therapy, 45*(10), 2307–2316. https://doi.org/10.1016/j.brat.2007.04.006.

Chalmers, A.-F. (1978). What is this thing called science? An assessment of the nature and status of science and its methods. *The British Journal for the Philosophy of Science, 29*(4), 389–392.

Chang, H. H., & Chuang, S.-S. (2011). Social capital and individual motivations on knowledge sharing: Participant involvement as a moderator. *Information & Management, 48*(1), 9–18. https://doi.org/10.1016/j.im.2010.11.001.

Chia-An Tsai, J., & Kang, T. C. (2019). Reciprocal intention in knowledge seeking: Examining social exchange theory in an online professional community. *International Journal of Information Management, 48*, 161–174. https://doi.org/10.1016/j.ijinfomgt.2019.02.008.

Chin, W. W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly, 22*(1), 1–8.

Chiu, C.-M., Wang, E. T. G., Fang, Y.-H., & Huang, H.-Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal, 24*(1), 85–114. https://doi.org/10.1111/j.1365-2575.2012.00407.

Colquitt, J. A., Scott, B. A., Rodell, J. B., Long, D. M., Zapata, C. P., Conlon, D. E., ... Wesson, M. J. (2013). Justice at the millennium, a decade later: A meta-analytic test of social exchange and affect-based perspectives. *The Journal of Applied Psychology*. https://doi.org/10.1037/a0031757.

Combita Niño, H. A., Cómbita Niño, J. P., & Morales Ortega, R. (2018). Business intelligence governance framework in a university: Universidad de la costa case study. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2018.11.012.

Constantiou, I. D. (2009). Consumer behaviour in the mobile telecommunications' market: The individual' s adoption decision of innovative services. *Telematics and Informatics, 26*(3), 270–281. https://doi.org/10.1016/j.tele.2008.11.005.

Corti, L., den Eynden, V., Bishop, L., & Woollard, M. (2014). *Managing and sharing research data: A guide to good practice.* Sage Publications Ltd.

Deutsche Forschungsgemeinschaft (2017). *Deutsche forschergemeinschaft.* Retrieved fromwww.dfg.de.

Devarakonda, R., Palanisamy, G., Green, J. M., & Wilson, B. E. (2011). Data sharing and retrieval using OAI-PMH. *Earth Science Informatics, 4*(1), 1. https://doi.org/10.1007/s12145-010-0073-0.

Ernst, C.-P. H. (2015). *Risk hurts fun: The influence of perceived privacy risk on social network site usage. Factors driving social network site usage.* Springer Fachmedien Wiesbaden45–56.

Featherman, M. S. (2001). Extending the technology acceptance model by inclusion of perceived risk. *AMCIS 2001 Proceedings,* 148.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3.

Fecher, B., Friesike, S., & Hebing, M. (2015). What drives academic data sharing? *PloS One, 10*(2), Article e0118053. https://doi.org/10.1371/journal.pone.0118053.

Feijen, M. (2011). *What researchers want.* Utrecht: SURF-foundation.

Feng, Y., & Yan Tam, K. (2013). Gain and loss in system switching: A behavioral economics view to understand the joint effects of system usage performance on user satisfaction. *PACIS 2013 Proceedings*.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39. https://doi.org/10.2307/3151312.

Gray, P. H. (2001). The impact of knowledge repositories on power and control in the workplace. *Information Technology and People, 14*(4), 368–384. https://doi.org/10.1108/09593840110411167.

Gutman, J. (1997). Means-end chains as goal hierarchies. *Psychology & Marketing, 14*(6), 545–560. https://doi.org/10.1002/(SICI)1520-6793(199709)14:6<545::AID-MAR2>3.0.CO;2-7.

Hair, J. F. J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM). Long range planning*, *46*https://doi.org/10.1016/j.lrp.2013.01.002.

Hamann, K., Warneken, F., Greenberg, J. R., & Tomasello, M. (2011). Collaboration encourages equal sharing in children but not in chimpanzees. *Nature, 476*(7360), 328–331. https://doi.org/10.1038/nature10278.

Hamann, K., Warneken, F., & Tomasello, M. (2012). Children's developing commitments to joint goals. *Child Development, 83*(1), 137–145. https://doi.org/10.1111/j.1467-8624.2011.01695.

Higman, R., & Pinfield, S. (2015). Research data management and openness: The role of data sharing in developing institutional policies and practices. *Program, 49*(4), 364–381. https://doi.org/10.1108/PROG-01-2015-0005.

Homans, G. C. (1958). Social behavior as exchange. *The American Journal of Sociology*. https://doi.org/10.1086/222355.

Horvath, A., & Rajeev, A. (2015). Trust in cloud computing. *SouteastCon 2015* (pp. 01–08). . https://doi.org/10.1109/SECON.2015.7132885.

Hsu, M.-H., Ju, T. L., Yen, C.-H., & Chang, C.-M. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. *International Journal of Human-Computer Studies, 65*(2), 153–169. https://doi.org/10.1016/j.ijhcs.2006.09.003.

Huang, Q., Davison, R., & Davison, R. M. (2008). Knowledge sharing barriers at the individual level in a Chinese bank. *PACIS 2008 Proceedings,* 150.

Jarvenpaa, S., & Staples, D. (2000). The use of collaborative electronic media for information sharing: An exploratory study of determinants. *The Journal of Strategic Information Systems, 9*(2–3), 129–154. https://doi.org/10.1016/S0963-8687(00)00042-1.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society, 47*, 263–291.

Kankanhalli, A., Tan, B. C. Y., & Wei, K.-K. (2005). Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly, 29*(1), 113–143.

Kim, H.-W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo Bias perspective. *MIS Quarterly, 33*(3), 567–582.

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems, 43*(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009.

Kim, Y., & Zhang, P. (2015). Understanding data sharing behaviors of STEM researchers: The roles of attitudes, norms, and data repositories. *Library & Information Science Research, 37*(3), 189–200. https://doi.org/10.1016/J.LISR.2015.04.006.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101.

Kuula, A., & Borg, S. (2008). Open access to and reuse of research data-The state of the art in Finland. *Finnish Social Science Data Archive, 7*(31).

Lagrange, R. L., Ferraro, K. F., & Supancic, M. (1992). Perceived risk and fear of crime: Role of social and physical incivilities. *The Journal of Research in Crime and Delinquency, 29*(3), 311–334. https://doi.org/10.1177/0022427892029003004.

Lending, D., & Straub, D. (1997). Impacts of an integrated information center on faculty end-users: A qualitative assessment. *Journal of the American Society for Information Science, 48*(5), 466–471. https://doi.org/10.1002/(SICI)1097-4571(199705)48:5<466::AID-ASI12>3.0.CO;2-X.

Li, L., He, W., Xu, L., Ash, I., Anwar, M., & Yuan, X. (2019). Investigating the impact of cybersecurity policy awareness on employees' cybersecurity behavior. *International Journal of Information Management, 45*, 13–24. https://doi.org/10.1016/j.ijinfomgt.2018.10.017.

Liang, T., Liu, C.-C., & Wu, C.-H. (2008). Can social Exchange theory explain individual knowledge-sharing behavior? A meta-analysis. *Twenty Ninth International Conference on Information Systems*.

Link, G., Lumbard, K., Conboy, K., Feldman, M., Feller, J., George, J., ... Willis, M. (2017). Contemporary issues of open data in information systems research: Considerations and recommendations. *Communications of the Association for Information Systems, 41*(25), 587–610. https://doi.org/10.1016/j.anireprosci.2016.02.027.

Lyytinen, K. (2009). Data matters in IS theory building. *Journal of the Association for Information Systems, 10*(10), 715–720. https://doi.org/10.17705/1jais.00211.

Makani, J. (2015). Knowledge management, research data management, and university scholarship: Towards an integrated institutional research data management support-system framework. *VINE, 45*(3), 344–359. https://doi.org/10.1108/VINE-07-2014-0047.

Marett, K., & Joshi, K. D. (2009). The decision to share information and rumors: Examining the role of motivation in an online discussion forum. *Communications of the Association for Information Systems, 24*(4), 47–68. https://doi.org/10.17705/1CAIS.02404.

Meske, C., Wilms, K., & Stieglitz, S. (2019). Enterprise social networks as digital infrastructures – Understanding the utilitarian value of social media at the workplace. *Information Systems Management, 36*(4), 350–367. https://doi.org/10.1080/10580530.2019.1652448.

Monastersky, R. (2013). Publishing frountiers: The library reboot. *Nature, 495*(7442), 430–432. https://doi.org/10.1038/495430a.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192.

Ortoleva, P. (2010). Status quo Bias, Multiple priors and uncertainty aversion. *Games and Economic Behavior, 69*(2), 411–424. https://doi.org/10.1016/j.geb.2009.11.007.

Park, S. C., & Sung, Y. R. (2013). An empirical investigation of end-users' switching toward cloud computing: A two factor theory perspective. *Computers in Human Behavior, 29*(1), 160–170. https://doi.org/10.1016/j.chb.2012.07.032.

Perrier, L., Blondal, E., Ayala, A. P., Dearborn, D., Kenny, T., Lightfoot, D., ... MacDonald, H. (2017). Research data management in academic institutions: A scoping review. *PloS One, 12*(5), 1–14. https://doi.org/10.1371/journal.pone.0178261.

Piwowar, H. A. (2011). Who shares? Who doesn't? Factors associated with openly archiving raw research data. *PloS One, 6*(7), Article e18657. https://doi.org/10.1371/journal.pone.0018657.

Piwowar, H. A., Day, R. S., & Fridsma, D. B. (2007). Sharing detailed research data is associated with increased citation rate. *PloS One, 2*(3), Article e308. https://doi.org/10.1371/journal.pone.0000308.

Piwowar, H. A., & Vision, T. J. (2013). Data reuse and the open data citation advantage. *PeerJ, 1*, Article e175. https://doi.org/10.7717/peerj.175.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Polites, G. L., & Karahanna, E. (2012). Shackled to the status quo: The inhibiting effects of incumbent system habit, switching costs, and inertia on new system acceptance. *MIS Quarterly, 36*(1), 21–42.

Pries-Heje, J., & Pries-Heje, L. (2011). Designing virtual team building with a focus on social capital. In M. Hertzum, & C. Jørgense (Eds.). *SourceIT: Balancing sourcing and innovation in information systems development* (pp. 123–144). TAPIR Akademisk Forlag.

Príncipe, P., Rettberg, N., Rodrigues, E., & Elbæk, M. K. (2014). OpenAIRE guidelines : Supporting interoperability for literature repositories, Data Archives and CRIS. *Procedia - Procedia Computer Science, 33*(December 2009), 92–94. https://doi.org/10.1016/j.procs.2014.06.015.

Ranganathan, C., Seo, D., & Babad, Y. (2006). Switching behavior of mobile users: do users' relational investments and demographics matter? *European Journal of Information Systems, 15*(3), 269–276. https://doi.org/10.1057/palgrave.ejis.3000616.

Renzl, B. (2008). Trust in management and knowledge sharing: The mediating effects of fear and knowledge documentation. *Omega, 36*(2), 206–220. https://doi.org/10.1016/j.omega.2006.06.005.

Ribes, D., & Polk, J. (2014). Flexibility relative to what? Change to research infrastructure. *Journal of the Association for Information Systems, 15*(5), 287–305. https://doi.org/10.17705/1jais.00360.

Ringle, C. M., Wende, S., & Becker, J.-M. (2014). *SmartPLS3*.

Rode, H. (2016). To share or not to share: The effects of extrinsic and intrinsic motivations on knowledge-sharing in enterprise social media platforms. *Journal of Information Technology, 31*(2), 152–165. https://doi.org/10.1057/jit.2016.8.

Rountree, P. W., & Land, K. C. (1996). Perceived risk versus fear of crime: Empirical evidence of conceptually distinct reactions in survey data. *Social Forces, 74*(4), 1353–1376. https://doi.org/10.1093/sf/74.4.1353.

Rudolph, D., Thoring, A., & Vogl, R. (2015). Research Data Management: Wishful Thinking or Reality? *PIK - Praxis Der Informationsverarbeitung Und Kommunikation, 38*(3–4), 113–120. https://doi.org/10.1515/pik-2015-0009.

Sadiq, S., & Indulska, M. (2017). Open data: Quality over quantity. *International Journal of Information Management, 37*(3), 150–154. https://doi.org/10.1016/j.ijinfomgt.2017.

01.003.
Samuelson, W., & Zeckhauser, R. (1988). Status quo Bias in decision making. *Journal of Risk and Uncertainty, 1*(1), 7–59. https://doi.org/10.1007/BF00055564.
Savage, C. J., & Vickers, A. J. (2009). Empirical study of data sharing by authors publishing in PLoS journals. *PloS One, 4*(9), 70–78. https://doi.org/10.1371/journal.pone.0007078.
Sayogo, D. S., & Pardo, T. A. (2013). Exploring the determinants of scientific data sharing: Understanding the motivation to publish research data. *Government Information Quarterly, 30*, S19–S31. https://doi.org/10.1016/j.giq.2012.06.011.
Schopfel, J., Chaudiron, S., Jacquemin, B., Prost, H., Severo, M., & Thiault, F. (2014). Open access to research data in electronic theses and dissertations: An overview. *Library Hi Tech, 32*(4), 612–627. https://doi.org/10.1108/LHT-06-2014-0058.
Schwartz, S. H. (1994). Are There Universal Aspects in the Structure and Contents of Human Values? *The Journal of Social Issues, 50*(4), 19–45. https://doi.org/10.1111/j.1540-4560.1994.tb01196.x.
Shaikh, R., & Sasikumar, M. (2012). Trust framework for calculating security strength of a cloud service. *International Conference on Communication, Information and Computing Technology, ICCICT 2012* (pp. 1–6). . https://doi.org/10.1109/ICCICT.2012.6398163.
Shreeves, S. L., & Cragin, M. H. (2008). Introduction: Institutional repositories: Current state and future. *Library Trends2, 57*(2), 89–97. https://doi.org/10.1353/lib.0.0037.
Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing, 66*(1), 15–37. https://doi.org/10.1509/jmkg.66.1.15.18449.
Stieglitz, S., Meske, C., Rudolph, D., & Vogl, R. (2014). Demand for Cloud services as an infrastructure in Higher education. *Proceedings of the 35th International Conference on Information Systems*.
Stieglitz, S., Wilms, K., Rudolph, D., & Vogl, R. (2018). Between termination and adoption – The Ex-users' Valley. *Proceedings of the 38th International Conference on Information Systems*.
Sweeney, J. C., Soutar, G. N., & Johnson, L. W. (1997). Retail service quality and perceived value. *Journal of Retailing and Consumer Services, 4*(1), 39–48. https://doi.org/10.1016/S0969-6989(96)00017-3.
van der Aalst, W. M. P., Bichler, M., & Heinzl, A. (2017). Responsible data science. *Business & Information Systems Engineering, 59*(5), 311–313. https://doi.org/10.1007/s12599-017-0487-z.
Verbaan, E., & Cox, A. M. (2014). Occupational sub-cultures, jurisdictional struggle and Third Space: Theorizing professional service responses to Research Data Management. *The Journal of Academic Librarianship, 40*(3), 211–219. https://doi.org/10.1016/j.acalib.2014.02.008.
Vines, T. H., Albert, A. Y. K., Andrew, R. L., Débarre, F., Bock, D. G., Franklin, M. T., ... Rennison, D. J. (2014). The availability of research data declines rapidly with article age. *Current Biology, 24*(1), 94–97. https://doi.org/10.1016/j.cub.2013.11.014.
Vogl, R., Rudolph, D., Thoring, A., Angenent, H., Stieglitz, S., & Meske, C. (2016). How to build a Cloud storage service or half a million users in Higher education: Challenges met and solutions found. *Proceedings of the 49th Hawaii International Conference on System Sciences,* 5328–5337.
Wang, X. (2013). Forming mechanisms and structures of a knowledge transfer network: Theoretical and simulation research. *Journal of Knowledge Management, 17*(2), 278–289. https://doi.org/10.1108/13673271311315213.
Wang, D., & Chan, H. C. (2012). A theory of instinctive information sharing. *Proceedings Annual Workshop of the AIS Special Interest Group for ICT in Global Development*.
Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly, 29*(1), 35–57.
Whyte, A., & Tedds, J. (2011). *Making the case for research data management.* Digital Curation Centre.
Wilms, K., Meske, C., Stieglitz, S., Rudolph, D., & Vogl, R. (2016). How to improve research data management. In (9735th ed.). S. Yamamoto (Vol. Ed.), *Human interface and the management of information: Applications and services: Vol. 9735*, (pp. 434–442). Cham: Springer. https://doi.org/10.1007/978-3-319-40397-7_41 HIMI 2016. Lecture Notes in Computer Science.
Wilms, K., Brenger, B., López, A., & Rehwald, S. (2018). Open data in Higher education – What prevents researchers from sharing research data? *Proceedings of the 38th International Conference on Information Systems*.
Wilms, K., Stieglitz, S., Buchholz, A., Vogl, R., & Rudolph, D. (2018). Do researchers dream of research data management? *Proceedings of the 51st Hawaii International Conference on System Sciences,* 4411–4420.
Wilms, K., Stieglitz, S., & Müller, B. (2018). Feeling safe on a fluffy Cloud – How Cloud security and commitment affect users' switching intention. *Proceedings of the 38th International Conference on Information Systems*.
Yang, Y., Liu, Y., Li, H., & Yu, B. (2015). Understanding perceived risks in mobile payment acceptance. *Industrial Management & Data Systems, 115*(2), 253–269. https://doi.org/10.1108/IMDS-08-2014-0243.
Zeithaml, V. (1988). Consumer perceptions of price, quality, and value: A means-. *Journal of Marketing, 52*(3), 2. https://doi.org/10.2307/1251446.